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Managing quality, supplier selection, and cold-storage contracts in agrifood supply chain through stochastic optimization

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Abstract

The quality of such processed agrifood products as dehydrated apple is related to the quality and variety of fresh harvested products and connected with wastage reduction throughout the agrifood supply chain. For this purpose, cold-storage management is important to avoid or mitigate the quality decay of fresh products stored in refrigerated systems. This paper explores the benefits of a two-stage stochastic programming model for product quality through the selection of producers and the management of cold storage to mitigate deterioration and guarantee the maintenance of quality. A case study with real data from an agribusiness company is presented in the case study to illustrate and assess the suitability of the stochastic approach. Uncertainty regarding the conversion rate of fresh apples into the final dehydrated product and the purchase cost of the apples in the system are represented through scenarios generated from historical data. Recourse actions include the purchase of additional fruit and renting of additional cold stores to meet the demand. Based on the different scenarios, the value of the stochastic solution shows that modeling and solving the proposed stochastic model minimizes costs by an average of around 6.4%. In addition, the expected value of perfect information demonstrates that using a proactive strategy could reduce costs by up to 9%. These results ensure the applicability of this model in practice before and during the harvesting season for planning and replanning as uncertainty is revealed under a rolling horizon.

Keywords: supply chain; dried apple; two-stage mixed 0-1; agro-industry; tactical planning

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1. Introduction

In recent years, the food industry has played an essential role in human society. Accordingly, agri-food supply chains (ASCs) in general and fruit supply chains (FSCs) in particular have grown significantly, fueled by increasing demand for healthier and greener lifestyles (Soto-Silva et al., 2016). The structure of modern FSCs may vary regarding the number of agents collaborating in the different stages. These are very similar in all ASCs, and involve farming (i.e., land cultivation, fruit production, and harvesting), warehousing, processing, packaging, and transportation to distribution centers, as shown in Fig. 1 (Soto-Silva et al., 2017; Villalobos et al., 2019; Jabarzadeh et al., 2020). In general, the principal agent in the FSC operation (as in many other ASCs) is the packing or processing plant as that is where offer and demand concur. The demand for fruit is mainly for fresh consumption and these products are traded by retailers, distributors, or exporters, but also processed by other industries to meet end-consumer demand (Fig. 1). Coordination of farmers and warehouse facilities with processing plants is even more critical when they belong to independent companies. At the beginning of the season, processing plants have to make relevant tactical decisions, such as the selection of enough suppliers and cold storage to ensure procurement to maintain the processing plant to operate until the following season. This forces other agents to coordinate with these plants (Soto-Silva et al., 2017; Flores and Villalobos, 2020). In this context, the selection of suppliers aims to ensure the quantity and quality of fresh products and enough cold storage to preserve quality until the fruit is packed or processed (Paam et al., 2019). Depending on the capacity for preserving fresh product preservation and the cold-storage technology, a processing plant can operate through until the following harvest. This happens in FSC with pears and apples (Nadal-Roig and Plà-Aragonés, 2015; Soto-Silva et al., 2017). Regarding the selection of suppliers and production contracts, processing plants have to identify reliable producers. Selection is complicated, and considerable time is required to achieve stable relationships between good producers and the processing plant (Anojkumar et al., 2014; Aouadni et al., 2019). With respect to the renting of cold storage, processing plants have to book facilities with a range of refrigeration technologies enabled to store the purchased raw material until it is processed. Some authors (Verdouw et al., 2010;

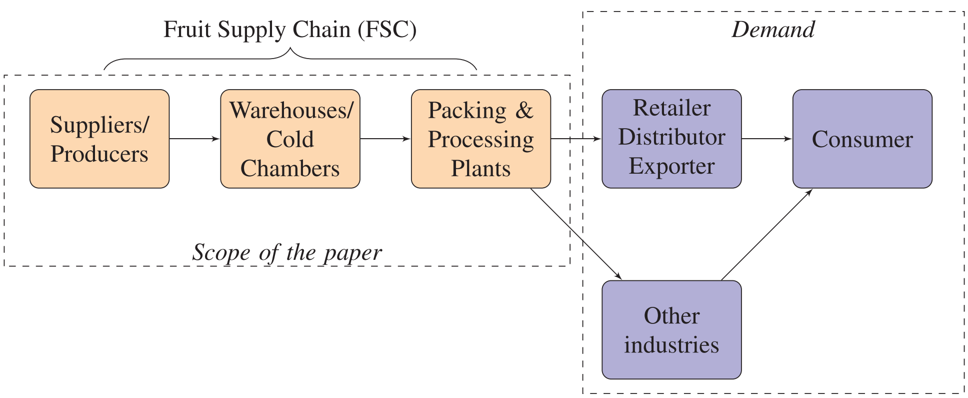


Fig. 1. Scope of the paper and flow of product through the fruit supply chain covering the main agents, similar to other agri-food supply chains. Arrows involve transportation between agents.

Paam et al., 2019) point out the necessity for proper storage handling with controlled conditions to prolong the profitability of fresh products, since these conditions preserve the quality longer, reduce spoilage, and so generate competitive advantages (Narasimhan and Mahapatra, 2004; Blackburn and Scudder, 2009; Aung and Chang, 2014b; Soto-Silva et al., 2017; Zhong et al., 2017). The quality of processed agrifood products is related to the quality and the variety of fresh harvested products. Special consideration for product quality requires more controlled storage conditions, delivery deadlines, and minimizing processing losses due to deterioration (Dabbene et al., 2008; Verdouw et al., 2010; Amorim et al., 2012; Nakandala et al., 2016; Song and Ko, 2016; Muriana, 2017; Salihoglu et al., 2018; Suthar et al., 2019). Transportation from the farms to cold storage, and from there to the processing plant, is normally outsourced to third parties and is also a production cost to consider for the FSC.

The management of these interrelated elements (quality, supplier selection, and cold storage) is difficult when planning production. Many classical planning models related to ASC and FSC consider all parameters deterministic (Soto-Silva et al., 2016; Flores and Villalobos, 2020). However, while this assumption could often be reasonable and a good approximation, there is always uncertainty in agriculture due to a range of factors. These include biology, disease, climate, and the market, plus those related to the complexities of logistics (Borodin et al., 2016; Soto-Silva et al., 2016; Liu et al., 2018; Jabarzadeh et al., 2020), which make the underlying supply chain more complicated and harder to manage than others (Ahumada and Villalobos, 2009; Villalobos et al., 2019). These challenges generate a need for more accurate and efficient decision-making tools to assist chain managers considering rapid adjustments at the operational or tactical level (Lowe and Preckel, 2004; Ahumada and Villalobos, 2009; Akkerman et al., 2010; Catalá et al., 2013, 2016; Villalobos et al., 2019; Gómez-Lagos et al., 2020). That is why, in this paper, we propose a tactical planning stochastic optimization model for a processing plant considering agricultural product quality through the selection of producers and the management of cold storage to mitigate deterioration and guarantee the preservation of quality. Without losing general overview and for illustrative purposes, we focus on the apple industry. This paper adopts the perspective of processing plant managers at around the beginning of the harvesting season. They have to agree production contracts with producers and cold-storage contracts with warehouse managers to fulfill a demand frequently already committed to retailers, exporters, or distributors, as shown in Fig. 1. Other decisions affecting quality, such as cultivation or harvest planning, are beyond the scope of this paper. Then, we formulate a two-stage stochastic optimization model with recourses (Kall, 1994), where the first-stage decision variables (i.e., here and now) represent proactive decisions taken before the uncertainty is revealed. These include the purchase of fresh produce, that is, apples, or the renting of cold storage to keep the processing plant operating throughout the season. On the other hand, the second-stage or recourse variables (i.e., wait and see, *WS*) represent reactive decisions made in recourse or response to compensate for the decisions made in the first stage. These cover additional purchases of produce and renting additional cold storage to meet final processed product demand after the uncertainty in quality is revealed.

The paper is structured as follows. There is a summary of publications relevant to this study focused on FSC management optimisation in Section 2. Section 3 describes the activities involved in the purchase and storage of fresh produce for processing in an FSC. Section 4 presents the two-stage stochastic optimization model formulation for purchase and storage decisions. The model considers a list of farmers, some private companies offering storage capacity, a fleet of trucks in charge of transportation, and the total annual demand for the processed product. In Section 5, a case study is presented to validate the model with the data available from a dehydration company in the Maule Region of Chile. The results are presented and discussed. Finally, in Section 6, the conclusions are presented, and future research is indicated.

2. Literature review

The globalization of food production, logistics, and consumption and increasing demand for healthier and more nutritious food have increasingly evolved toward complex FSCs as part of ASC networks, which play a central role in ensuring food products of high and consistent safety and quality. As a general approach, Zhong et al. (2017) present an in-depth review of past, present, and future research into food supply chain management, highlighting systems, implementations, and practical implications. The review covers 192 articles, many related to ASCs but fewer about FSCs. A more specific review of operational research models applied to FSCs showed publications focused on different stages of the chain (Soto-Silva et al., 2016). In fact, operations research and mathematical models are common tools to assist the decision-making processes and are used to build data-driven decision support systems (DSS) and IT-based solutions. Hence, mixed-integer linear programming (MIP) models are widely used to solve the proper plant location problem, a distribution network configuration, improving planning and scheduling, maximizing profit, or minimizing production cost (Plà et al., 2014).

Regarding FSC, Soto-Silva et al. (2016) remarked on the methods applied to supplier selection have focused mainly on multicriteria analysis, mathematical programming, and artificial intelligence in agreement with other authors (Chai et al., 2013; Ivanov et al., 2017; Aouadni et al., 2019). Different authors have pointed out that the main criteria used for decisions about the selection of suppliers are quality, delivery time, price, manufacturing capacity, service, management, technology, research and development, flexibility, reputation, relationship, risk, safety, and the environment (Guneri et al., 2009; Zimmer et al., 2016; Aouadni et al., 2019). Other authors (Anojkumar et al., 2014) advocate determining logical and straightforward selection criteria to make efficient decisions in the shortest time. Regarding cold storage, the critical decision is the capacity and type of cold storage to be rented and later the coordination of the opening and closing of the cold store according to the refrigeration technology used (Soto-Silva et al., 2016). As mentioned above, product quality is related to the optimal ripeness of the fruit and requires controlled storage conditions to minimize losses due to deterioration (Muriana, 2017; Paam et al., 2019; Céline et al., 2020). Hence, a first linear programming model to minimize the loss of fruit quality when stored in different types of cold storage was proposed by Broekmeulen (1998). For transportation decision models, the formulation of integer linear programming models minimizing processing plant transportation costs is the most frequent method. For instance, this involves emphasizing storage costs for the finished product (Kawamura et al., 2006), cold-storage management (Paam et al., 2019), or determining the use of means of transport for multiproduct supply chains (Lamsal et al., 2016). Other studies take the degradation of quality in the supply chain into account (Rong et al., 2011; Muriana, 2017; Céline et al., 2020; de Moraes et al., 2020) and consider the transportation from producers to retailers (Bortolini et al., 2016; Nakandala et al., 2017). Routing problems are often found in the distribution of perishable foods (Osvald and Stirn, 2008; Song and Ko, 2016; Soysal et al., 2018)

Table 1
Overview of stochastic programming approaches to decision-making problems in fresh ASC, dealing with some aspects common to FSCs

Authors	Scope	Modelling approach	Purpose
Ahumada and Rene Villalobos (2019)	Fresh fruits	Two-stage MIP	Planting decisions and revenue maximization
Banasik et al. (2019)	Mushrooms	Multiobjective two-stage LP	Production planning and harvesting decisions
Mogale et al. (2018)	Grain	MINLP	Transport and storage
Azadi et al. (2019)	Perishable products	Two-stage MIP	Suppliers selection
Mateo et al. (2016)	Fresh vegetables	Two-stage MIP	Production planning and supplier selection
Amorim et al. (2016)	Perishable products	Two-stage MIP	Supplier selection

LP, linear programming; MINLP, mixed-integer nonlinear programming; MIP, mixed-integer programming.

considering a distribution center (Eskigun et al., 2005), while in fruit production or processing routing problems are less common (Nadal-Roig and Plà-Aragonés, 2015; Suthar et al., 2019). Decision models integrating tactical decisions about production, transport, and route planning are still scarce, and applications to real cases even more limited (Mula et al., 2010; Díaz-Madroñero et al., 2015; Soto-Silva et al., 2016; Ahumada and Rene Villalobos, 2019). Other decision models dealing with technical particularities combining cold storage and product quality, such as the optimal temperature for perishable foods or frozen fruit (McHugh and Senesi, 2000; Róth et al., 2007; Aung and Chang, 2014a) or those considering the environmental issues of transportation (Bortolini et al., 2016; Nakandala et al., 2016; Soysal et al., 2018), are beyond the scope of this study.

Most of the publications mentioned above are based on deterministic models, demonstrating that decision-making models under uncertainty are one of the main challenges in the agricultural sector (Plà et al., 2014; Behzadi et al., 2018; Zhao et al., 2020). Borodin et al. (2016) discussed how uncertainty is handled in ASC models, observing the growing trend for including stochastic components, with the most popular approach being stochastic programming followed by robust optimization. The advantage of stochastic programming is that it allows the modeler to deal with the uncertainty of some parameters via scenarios (Birge and Louveaux, 1997; Ruszczynski and Shapiro, 2003), and has been proposed for successfully solving a range of problems, both in industrial fields (Wallace and Ziemba, 2005) and more recently in the ASC (Onggo et al., 2019; Carvajal et al., 2019; Albornoz et al., 2020; Flores and Villalobos, 2020; Guarnaschelli et al., 2020; Nadal-Roig et al., 2020). An extended summary of published research into the realm of food supply chains with interest for our study in the FSC and including a stochastic programming approach is presented in Table 1.

Summing up this section, it demonstrates the following gaps in the literature and is the motivation of this paper:

- From over a hundred papers reviewed by Borodin et al. (2016), only a couple were related to FSCs (Tan and Çömden, 2012; Munhoz and Morabito, 2014).
- Across all deterministic mono- or multiobjectives models, LP and MIP are the most frequently used to solve supplier selection or storage decision.

- Stochastic programming can deal with uncertainty in FSCs and is underused.
- To the best of our knowledge, no previous study has tackled the supplier selection and storage decisions under uncertainty.

3. Fruit supply chain overview

Fruit is consumed fresh or processed. Typical FSCs are represented by independent agents. These include suppliers (orchards owners), packing or processing plants, warehouses, distributors, other industries, and consumers collaborating for the same purpose. The coordination of the FSC is assumed by a processing or packing plant, as presented in Fig. 1. The structure of the chain as presented is generally valid for most fruit products, since the differences lie in the time between harvesting and processing. Apples and pears are examples of fruit available all year round. It is harder to slow the ripening process in cold storage of most other fruits, such as plums or cherries, and vegetables (Nadal-Roig and Plà-Aragonés, 2015).

Soto-Silva et al. (2017) supply an in-depth information about the actors and the flow of raw material involved in the apple supply chain. According to them, purchase and storage decisions are important in the FSC since, according to Soto-Silva et al. (2017), the main production cost components of a processing plant are the purchase, transportation, and storage of raw material (85%), and the rest is energy (5%), salaries (5%), and others costs (5%).

3.1. Suppliers selection

For instance, in the case of apples, the processing plant manager would like to ensure the purchase of all the fresh apples needed to keep the processing plant operating (e.g., in the case of dehydrated apple-processing plants) at full capacity with minimal loss until the next harvest season. However, the processed quality of the apples is uncertain as it depends on variety, freshness, ripeness, fruit damage, and storage conditions. Thus, poor quality of the apples can be caused in the field (damage when harvesting and transporting, bad weather, or inadequate ripeness), bad storage conditions (inappropriate temperature or atmosphere control), or a combination of both.

The apples are picked up by producers who are generally the orchard owners. For instance, a conventional processing plant with a capacity for approximately 30,000 t of fresh apples can efficiently deal with about 250 producers who can offer six varieties of apple suitable for different storage periods (Soto-Silva et al., 2017). The fruit is collected in bins with a capacity of 0.380 t. In agreement with the producer, the processing plant collects the bins from the orchard and processes them for payment, accounting, and selection (González-Araya et al., 2015). Later on, the fruit is sent to different cold-storage units, either in refrigerated chambers belonging to the plant or rented ones. The decision to store the fruit in a specific refrigerated chamber is made by the processing plant on receiving the fruit. During the harvest season, prices depend on the demand for fresh fruit and can be lower or higher than out of season. Note that the processing plants compete for fresh apples with packing plants and suppliers of fresh fruit for human consumption. After the harvest season, the amount of fresh fruit available on the market decreases by around 80% and this directly affects purchase prices. Soto-Silva et al. (2017) claim that the prices per kilogram could rise by around 30%.

These market conditions generate uncertainty in the supply of fresh fruit. As any corrective action to purchase more fruit beyond the harvesting season could represent an extra or lesser cost depending on the market, purchasing decisions are more critical when processing plants, warehouses, and orchards belong to different private companies or farmers and which have to coordinate with each other (Nadal-Roig and Plà-Aragonés, 2015).

3.2. Cold-storage contracts

The type of cold store where the fruit is kept must also be selected. Keeping fruit in cold storage longer than the specified period may cause losses (Paam et al., 2019). Fruit, such as apples, has to be segregated according to the storage period considered (short-, medium-, or long-term period). This segregation is done according to the variety and physiological indices that are checked by professionals in the reception area (González-Araya et al., 2015; Soto-Silva et al., 2017). Among the most common indicators are the Brix degree, pressure, starch index, and physical damage. In general, good-quality fruit, that is, with the right quality indexes, implies longer storage capability with lower deterioration.

The storage period depends on the type of cold chamber and the technology used. Moreover, the ripening process for all the stored fruit must be controlled by the refrigeration system (Nadal-Roig and Plà-Aragonés, 2015). The cold technologies available are conventional (CR) with only thermostatic control, smart fresh (SF) adding a phytoregulator diffusion system that minimizes the synthesis of ethylene and delays maturation, and controlled atmosphere (CA) where the concentrations of oxygen, carbon dioxide, and nitrogen are regulated along with the temperature and humidity. CR, SF, and CA allow the fruit to be preserved for periods of about three, six, or nine months (short-, medium-, and long-term periods), respectively. Generally, processing plants need more than one warehouse to keep fruit stored for processing throughout the year, from season to season. A warehouse can have chambers with different cold technologies. It is common and advisable to have one type of fruit stored in a cold chamber at a time (González-Araya et al., 2015; Paam et al., 2019). When a processing company does not have enough capacity for cold storage, it must lease it. The storage available for rent is a scarce resource as it is sought after by different agro-industrial processing companies related to fruit, vegetables, and meat products competing on the same market. This situation may imply looking for more expensive storage or in more distant locations. Then, an accurate decision to evaluate cold-storage contracts should be made at the beginning of the season, or even before. Obtaining enough storage contracts to fulfill the needs of the processing plant will be a competitive advantage for a company. Storage is usually charged per tonnes of fruit in function of the refrigeration technology and, hence, corresponds to a variable cost. On the other hand, there is a fixed storage cost related to the administrative costs of renting cold storage.

3.3. Transportation

Transportation from the orchards to the processing plant for selection and from the processing plant to the warehouses is usually outsourced since it is expensive to maintain a fleet of trucks with the maintenance and drivers' salaries (González-Araya et al., 2015). However, depending on the country, it is also common for producers be in charge of delivering fruit (i.e., apples) to the processing plant (Nadal-Roig and Plà-Aragonés, 2015). Payment policies vary. Among the most common are payment per kilogram or bin transported, by kilometer covered, or even an agreed fixed quantity for the whole season. However, transport costs generally have two components: a variable cost that depends on the quantity of fruit transported and the distance traveled, and a fixed cost corresponding to the transportation freight. In practice, processing plant managers are in charge of the logistic planning and transport of fresh fruit from suppliers to the processing plant and from the processing plant to the warehouses. They estimate a variable cost as a unit value per tonne transported considering the distance between the processing plant and the suppliers, and from the processing plant to the warehouses. Regarding the fixed cost, the total load capacity of each type of truck is also considered.

3.4. The dehydrated apple supply chain

The dehydration industry has undergone rapid growth in recent years and represents an interesting alternative for diversifying fruit-related products (González-Araya et al., 2015). Most of the production is already committed at the beginning of the season, so there is no or little uncertainty regarding the amount of dried apple to produce. There is uncertainty regarding the amount of fresh apple needed to satisfy this demand for the dried end product. In contrast, in the FSC oriented to marketing fresh fruit and run by a packing processing plant, the same quantity of fruit stored is later packed and sold. Thus, the demand for a dehydration processing plant implies a mass reduction from the weight of the fresh fruit by processing, while the relationship between both quantities (fresh and dried) is the so-called conversion rate. The conversion rate (fc) of fresh apple into dehydrated apple is an uncertain parameter directly related to its quality, and this varies from season to season (Soto-Silva et al., 2017). A reference in the industry is $fc = 1/11$ representing 11 kg of fresh apples is needed to obtain 1 kg of dehydrated apples. The conversion rate is important as it determines the amount of fresh apples to be purchased to meet the demand for the dried products. Hence, a better conversion rate allows a reduction in the weight of fresh fruit to be purchased and still meet the same demand for dried apples.

3.5. The role of the processing plant manager

The processing plant manager represents the decision maker who has to coordinate the supply chain to permit the plant to operate by selecting suppliers, agreeing purchase and storage contracts, with the aim of ensuring enough storage space for the raw material purchased and organizing transport to the processing plant. The timeline of the decisions taken by the processing plant manager are represented schematically in Fig. 2. The figure illustrates the main activities (harvesting and warehousing) interacting with processing plant operation over a typical season (one year) in a FSC. It is shown where the uncertainty about fc and CC appear and accordingly, where the processing plant manager can take corrective measures. Note that the average duration of the harvest season is approximately three months (the initial ones) and the processing plant operation will depend on

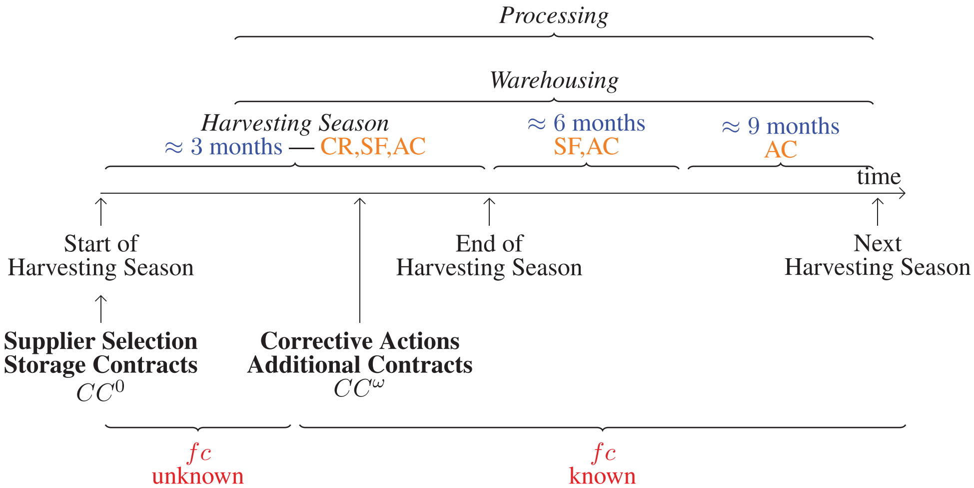


Fig. 2. Timeline for processing plant operation regarding warehousing with different cold technology options (CR, conventional; SF, smart fresh; and CA, controlled atmosphere). First-stage decisions are made when fc is unknown and corrective actions are taken once uncertainty about fc and CC^ω has been revealed.

the procurement of raw material from warehouses over a maximum of the following nine months. In this situation, the plant manager starts planning the season before the harvest begins. That is when most suppliers are selected and storage contracts are agreed. These decisions are made based on expected production and quality estimates based on samples in the field. In the case of dehydration processing plants, no information about the conversion rate of the fresh product, fc, is known beyond estimates from historical records and the manager's experience. Once the season starts, the fruit purchased is sent to the processing plant after harvested for sorting and storing under different cold technologies: short term (CR), medium term (SF), and long term (AC). As the fruit is processed, the first information about the conversion rate becomes available. At the same time, the market also offers information about demand, sales prices, availability of additional storage, and confirms production forecasts or update them. This evidence gives the plant manager indications for adopting corrective measures, such as negotiating additional contracts with suppliers or warehouses to ensure the operation of the processing plant. Once the harvest season is over, there is no produce in the fields and it is extremely difficult to buy raw material for the processing plant if this has run out. At the same time, most of the raw material stored is already committed and the cold technology involved determines the duration of storage, that is, CR three months, SF six months, or AC nine months. The objective for processing plants dealing with fresh fruit products such as apples or pears is to purchase enough fruit to keep them operating until the next harvest season.

4. Stochastic modeling approach

The nomenclature used to model the input parameters and the required sets belonging to the dried-apple supply chain is described below. The tactical and operational decisions are also presented.

Nomenclature

Indices and index sets (positive integers)

$p \in P$ Set of available producers.
$q \in Q$ Set of fresh fruit varieties in the orchards. For example, in the apples context (case study) is 1: Royal gala, 2: Granny Smith, 3: Fuji, 4: Braeburn, 5: Pink Lady and 6: Red.
$t \in T$ Set of cold storage types regarding maximum storage time being 1: conventional technology (upto three month), 2: Smart fresh (upto six month) and 3: controlled atmosphere (about nine month and more).
$n \in N$ Set of the maximum number of cold chambers inside a warehouse.
$c \in C$ Set of warehouses.
$l \in L$ Set of truck-trips transporting fruit from warehouses to the processing plant.
$\omega \in \Omega$ Set of different uncertain scenarios (representing the second stage). The upper script ^{0} is used to represent the first stage.

Parameters

π^{ω} Probability of scenario ω.
fc^{ω} Conversion factor of scenario ω related to fruit quality and food loss
CC^0_{pq} Cost for purchasing and transport in the first stage; from a producer p and the variety q.
CC^{ω}_{pq} Cost for purchasing and transport in the second stage; from a producer p and the variety q under scenario ω.
CM_p Cost to maintain a producer p.
CFT_l Cost for using truck l.
CE_{cnq} Cost of using room n in warehouse c to store a variety q.
TE_{cn} Type of cold tech used inside room n belonging to warehouse c.
D_t Minimum demand for processed product (e.g. dried apple) to be met during the three storage periods related to the cold storage types (lasting around three, six or nine months).
O_{pq} Amount of raw material from variety q produced by producer p.
CF^0_{cn} Fixed cost of using room n in warehouse c, in the first stage.
CF_{cn} Fixed cost of using room n in warehouse c, in the second stage, under all scenarios.
CA_c Fixed cost for using rooms belonging to warehouse c.
$QMax_l$ Maximum capacity of truck l.
WC_{cn} Capacity of room n inside warehouse c

Decision variables for the first stage

XP^0_{pq} Binary variable 0,1 indicating if variety q is purchased from producer p.
ME^0_{cnqt} Binary variable 0,1 indicating if cold storage chamber n inside warehouse c is contracted to store fruit of variety q and cold storage type t.

Decision variables for the first stage

Z^{ω}_p Binary variable 0,1 indicating if producer p is selected as supplier.
XP^{ω}_{pq} Binary variable 0,1 indicating if variety q is purchased from producer p under scenario ω

A_c^{ω} Binary variable 0,1 indicating if warehouse c is contracted under scenario ω.
ME_{cnqt}^{ω} Binary variable 0,1 indicating if cold storage chamber n inside warehouse c is contracted to store fruit of variety q and cold storage type t, under scenario ω.
YC_{lcn}^{ω} Number of trips from the processing plant using truck l, under scenario ω.
W_{pqt}^{ω} Amount of fresh fruit (i.e apples) purchased from producer p that are used to satisfy the demand for variety q and and cold storage type t, under scenario ω.
X_{cnqt}^{ω} Amount of fresh fruit (i.e apples) in cold storage chamber n inside warehouse c to store fruit of variety q and cold storage type t, under scenario ω.

The mathematical model based on the parameters listed in the nomenclature is presented in this section considering the operation of an FSC involved with the quality of the raw material represented by the conversion factor, supplier selection from a set of available producers in view of agreed purchase contracts, and cold storage available for rent in warehouses with installations with the three different cold technologies:

$$\min \quad C^0 + \sum_{\Omega \in \omega} \pi^{\omega} C^{\omega};$$

$$\text{s.t.} \quad Z_p^{\omega} \geq (XP_{pq}^0 + XP_{pq}^{\omega}), \quad \forall \omega \in \Omega, \ \forall p \in P, \ \forall q \in Q \tag{1a}$$

$$XP_{pq}^0 + XP_{pq}^{\omega} \leq 1, \quad \forall \omega \in \Omega, \ \forall p \in P, \ \forall q \in Q \tag{1b}$$

$$\sum_{t \in T} W_{p,q,t}^{\omega} = (XP_{pq}^0 + XP_{pq}^{\omega}) * O_{p,q}, \quad \forall \omega \in \Omega, \ \forall p \in P, \ \forall q \in Q \tag{1c}$$

$$\sum_{q \in Q} \sum_{p \in P} W_{p,q,t}^{\omega} * fc^{\omega} \geq D_{t'}, \quad \forall \omega \in \Omega, \ \forall t, t' \in T \ : \ t \leq t' \tag{1d}$$

$$\sum_{q \in Q} \sum_{t \in T} (ME_{cnqt}^0 + ME_{cnqt}^{\omega}) \leq 1, \quad \forall \omega \in \Omega, \ \forall c \in C, \ \forall n \in N \tag{1e}$$

$$X_{cnqt}^{\omega} \leq WC_{cn}(ME_{cnqt}^0 + ME_{cnqt}^{\omega}), \quad \forall \omega, c, n, q, t \in \Omega, C, N, Q, T \tag{1f}$$

$$\sum_{n \in N} \sum_{t \in T} \sum_{q \in Q} ME_{cnqt}^0 + ME_{cnqt}^{\omega} \leq |C| * A_c^{\omega}, \quad \forall \omega \in \Omega, \ \forall c \in C \tag{1g}$$

$$\sum_{t \in T} \sum_{q \in Q} X_{cnqt}^{\omega} \leq QMax_l * YC_{lcn}^{\omega}, \quad \forall \omega, c, n, l \in \Omega, C, N, L \tag{1h}$$

$$ME_{cnqt}^0 = 0, \quad \forall q, c, n, t \in Q, C, N, T \ : \ t < TE_{cn} \tag{1i}$$

$$ME^{\omega}_{cnqt} = 0, \quad \forall \omega, q, c, n, t \in \Omega, Q, C, N, T \ : \ t < TE_{cn} \tag{1j}$$

$$\sum_{c \in C} \sum_{n \in N} X^{\omega}_{cnqt} \geq \sum_{p \in P} W^{\omega}_{pqt}, \quad \forall \omega \in \Omega, \ \ \forall q \in Q, \ \ \forall t \in T. \tag{1k}$$

The constraints of the model (1) proposed in this section can be divided into two main blocks. The first block corresponds to the purchasing decisions and involves constraints (1a)–(1d). First-stage decisions for purchase are important for detecting the main producers to be selected as suppliers. The second block of constraints represents the storage decisions and involves constraints (1e)–(1j). A supplier of a variety or the renting of a cold chamber can only be done in one stage (see constraints (1b) and (1e)). Despite this, the two blocks are not independent, so constraint (1k) is required to ensure that the storage capacity is greater than or equal to the amount of apples purchased.

Let us consider the constraints related to the first block and corresponding to the supplier selection step. Constraint (1a) detects whether a producer is selected as a supplier for any variety. Thus, (1b) is required to coordinate purchase decisions in the first or the second stage. It is important to highlight that if a producer is selected to supply a variety of fresh fruit ($q \in Q$), all the fruit belonging to this variety must be purchased from this producer. This behavior is represented in (1c) when summing up to the total amount of fruit purchased.

Harvested fruit are transported to the processing plant for sorting and dispatch to a specific cold-storage chamber depending on the forecast storage period. The ripening characteristics of different fruit varieties vary and not all of them are suitable for long-term storage (e.g., red apples). In addition, selecting the suitable cold technology guarantees the quality of the fruit is maintained until processing. Hence, segregation of the fruit by the type of refrigeration ensures fruit quality and minimal losses summarized in the conversion factor fc^{ω}. Because of the uncertainty in the fc^{ω}, the exact amount of fruit (apples) needed to meet the fixed demand for the processed product (i.e., dried apples) for the operation of the processing plant all year round is unknown at the beginning of the harvest season. In this context, constraint (1d) represents the amount of fresh fruit to be purchased in order to fulfill the demand for processed product over time depending on the ripening characteristics and quality captured by the conversion factor. During the harvest season, the processing performance of the plant will enable the managers to know the real conversion factor of the fresh product and consider whether additional purchases are required. Note that fruit purchased to meet the long-term demand can also be used to cover short-term demand; see (1d). However, fruit corresponding to the short-term demand cannot be used to satisfy long-term demand (i.e., $t \leq t'$). Furthermore, storage time depends on the cold-storage technology, so a CA allows long-term storage, while conventional cold only allows short-term storage. In this context, constraint (1d) uses the indexes t and t' to ensure that short-term demand cannot be used to satisfy long-term demand, although the opposite is allowed. The same is used to set the order for opening cold chambers depending on the technology, that is, CR first, SF second, and CA third.

Regarding the second block constraints (the storage step) ensures that all the apples purchased can be allocated and stored in the selected warehouses with adequate cold technology; see (1f). Another constraint modeling usual practices is that only one variety of fruit can be stored in any given cold chamber, so (1e) is needed, and logically (1g) is used to guarantee that a cold chamber could be used only if its warehouse is selected. Here, transportation is modeled explicitly (1h) and fruit removed from cold storage is delivered to the processing plant by truck.

Last but not least, (1i) and (1j) are used to sort the fruit depending on the different cold-storage technology. This information is described in parameters TE_{cn}, CF^0_{cn}, CF_{cn}, and CE_{cnq}, which represent the types of cold storage in each room inside a warehouse and the costs of using these.

The objective function seeks to minimize processing plant costs associated with purchase, transport, and storage in both stages:

- The first-stage cost C^0 represents the contracts made at the beginning of the season related to suppliers (purchase and transport cost, CC^0_{pq}) and warehouses (storage cost, CF^0_{cn}):

$$C^0 = \sum_{p\in P}\sum_{q\in Q} CC^0_{pq} * XP^0_{pq} * O_{pq} + \sum_{c\in C}\sum_{n\in N}\sum_{q\in Q}\sum_{t\in T} CF^0_{cn} * ME^0_{cnqt}. \tag{2}$$

- The second-stage cost C^ω represents the corrective actions taken in each scenario when the uncertainty in fc and the derived cost are revealed:

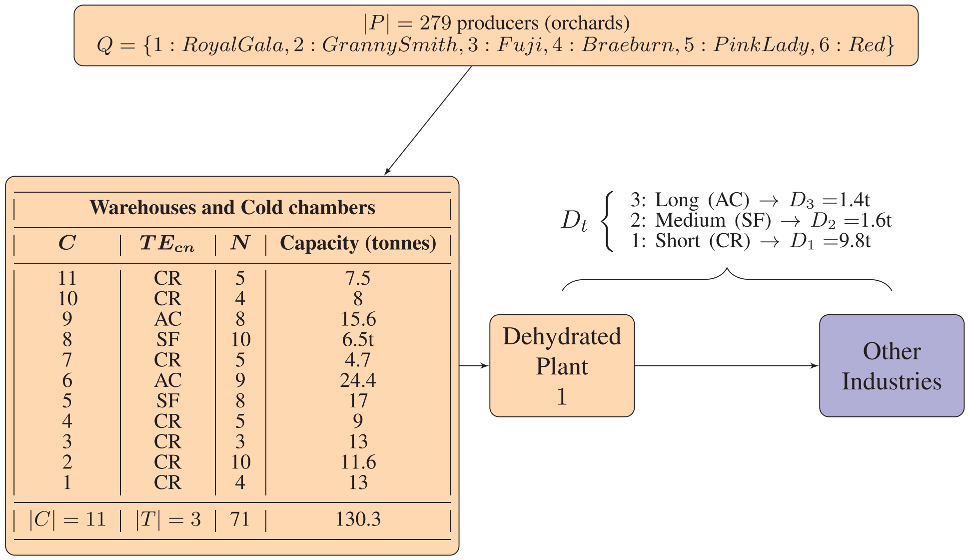
$$C^\omega = \sum_{p\in P}\sum_{q\in Q} CC^\omega_{pq} \times XP^\omega_{pq} \times O_{pq} + \sum_{p\in P} CM_p \times Z^\omega_p + \sum_{l\in L} CFT_l \times \sum_{c\in C}\sum_{n\in N} YC^\omega_{lcn}$$
$$+ \sum_{c\in C} CA_c \times A^\omega_c + \sum_{q\in Q}\sum_{t\in T}\sum_{c\in C}\sum_{n\in N}\left(CE_{cnq} \times X^\omega_{cnqt}\right) + \left(CF_{cn} \times ME^\omega_{cnqt}\right). \tag{3}$$

The generation of the stochastic scenarios lies in the raw material quality, represented by the conversion rate fc, and the purchase cost in the second stage, C^ω. These were selected for the design of the full range of scenarios (Table 3). Uncertainty can be modeled with a closer look at the historical data to show the range of the main random fluctuations. It was considered that a reasonable range of values was from 1:6 to 1:18. In this continuous space formed by this range of values, there are infinite possibilities to generate scenarios. To overcome this situation, the authors propose using the conditional scenario approach presented in Beltran-Royo (2017). This method computes and discretizes a set of conditional expectations of the random vector that models the uncertain problem parameters, thus providing an excellent approximation to the real solution. Therefore, using historical data and the know-how from company experts, we can decide the specific number of scenarios and the discretization of an extensive range of future possibilities assigning the corresponding probability of them happening. Thus, we proposed a discretization of 13 scenarios to represent the whole space. For this purpose, historical data on quality based on fc were analyzed and used to compose Table 3, which is introduced in the following section.

5. Case study: a dehydrated apple processing plant

5.1. Input parameters

The case study presented tries to shed light on the advantages of the stochastic approach and seeks to demonstrate the applicability of the proposed stochastic model to a real FSC. A case study



C	TE_{cn}	N	Capacity (tonnes)
11	CR	5	7.5
10	CR	4	8
9	AC	8	15.6
8	SF	10	6.5t
7	CR	5	4.7
6	AC	9	24.4
5	SF	8	17
4	CR	5	9
3	CR	3	13
2	CR	10	11.6
1	CR	4	13
$\lvert C\rvert = 11$	$\lvert T\rvert = 3$	71	130.3

Fig. 3. Main traits for the case study: number of available suppliers (producers, P); the apple varieties, Q; the number of warehouses, C; and cold chambers, N with cold technology (AC, SF, and CR) and warehouse capacity and the demand for the short, medium, and long terms.

from a leading Chilean agribusiness company is used to illustrate and assess the suitability of the proposed model. The data were gathered from a dehydration plant located in the Maule Region. It produces dried apple and sells all the production under contract to producers of breakfast cereals, muesli, and similar. Figure 3 shows the main dimensions of the case study considered.

The raw material (apples) can be purchased from the beginning to the end of the harvesting season, but the market prices change over the season, influenced by different factors. One of the most important of these factors is the quality of the apples related to losses of product captured by the conversion rate, fc, and market prices. Likewise, storage contracts can be signed throughout the season as long as there are facilities available. In this context, purchase managers make blind decisions at the beginning of the season without knowing the processing quality of the apples they have to buy, the evolution of market prices, or the storage capacity they need to contract. However, demand for dehydrated apple is almost constant, as all the production is committed or sold beforehand.

Table 2 shows the historical expectation of fc^{-1} and its variability in a dehydration processing plant from season to season. Based on that and on field sampling, the processing plant manager calculates prior expectations of fc^{-1} for the next season (Table 2). For instance, in 2008, a 23% increment in additional purchases of fruit was observed, representing 20% of the extra cost (i.e., US\$338,948.36) to meet the annual demand. The averaged deviation between 2006 and 2015 due to poor-quality apples was US\$125,560.58 and resulted in a worse-than-expected conversion rate. Hence, as shown in Table 2, in the year when this happens the processing plant manager has to seek to buy more fresh fruit, and also to rent additional cold stores, so incurring additional expenses.

Historical data (Table 2) provide strong evidence about the impact of variability on the amount of fruit to process yearly and the necessity to consider these aspects in the optimization model.

Table 2
Variation over time of the expected and observed conversion rate, fc^{-1}, for the dehydration processing plant from years 2006 to 2015 including the amount of fresh apple purchased, dried apple produced, and revenue

Year	Purchased Apples (1000 t)	End product (1000 t)	fc^{-1} expected	fc^{-1} real	Variation (%)	Variation (US$1000)
2006	22.99	1.97	10.49	11.68	11	151.74
2007	21.30	1.84	10.70	11.60	8	102.22
2008	24.56	1.79	11.19	13.76	23	338.98
2009	17.48	1.70	10.62	10.38	−3	−31.46
2010	23.85	2.15	10.60	11.09	5	71.55
2011	22.28	2.01	10.54	11.11	5	66.84
2012	26.29	2.39	10.49	10.99	5	78.88
2013	21.06	1.82	10.49	11.58	10	126.36
2014	20.56	1.74	10.52	11.85	13	160.40
2015	19.80	1.63	10.46	12.18	16	190.09

Table 3
Probability π^{ω} and values for the uncertain parameters in each scenario: conversion rate, fc^{ω}, and purchase cost in the second stage; CC^{ω} besides the purchase cost in the first stage; and the variation regarding the purchase cost in the second stage

Ω	π^{ω} (%)	fc^{ω}	CC^{0} ($)	%	CC^{ω} ($)
1	04	1:06	12.5	−45	06.87
2	04	1:07	12.5	−31	08.62
3	06	1:08	12.5	−25	09.37
4	09	1:09	12.5	−19	10.12
5	10	1:10	12.5	−16	10.50
6	16	1:11	12.5	−12	11.00
7	15	1:12	12.5	10	13.75
8	12	1:13	12.5	12	14.00
9	08	1:14	12.5	16	14.50
10	07	1:15	12.5	20	15.00
11	04	1:16	12.5	33	16.62
12	04	1:17	12.5	42	17.75
13	01	1:18	12.5	49	18.62

Furthermore, 86% of the cold-storage capacity in Chile is CR or SF, and the rest CA, the latter being more expensive but permitting the longest preservation (by nine months). Therefore, although there is a minor variation in hiring cost over the year, it is true that the offer of cold stores decreases considerably during the harvest season. Contract agreements progress over time, with the risk of exhausting the supply in the surroundings of the processing plant.

Table 3 shows the 13 scenarios generated and the probability of each one. In this study, we estimate the demand for dried apple based on the historical average for the company. However, apple purchases are correlated with the conversion factor fc. This fluctuates from season to season and leads to the adoption of corrective actions and so, the variability in the amount of apples purchased over time. Thus, the conversion factor fc^{ω} represents the main stochastic component of the problem, besides the purchase cost, once the harvesting season has started. Thus, according to Table 3, scenario $\omega = 1$ is the most optimistic because it considers the apples with the highest quality, best fc, and lowest price (−45%) compared with the first stage, CC^0.

The second-stage purchase costs was assumed to be scenario-dependent (see CC^ω in Table 3). In particular, high quality is related to an excellent harvest season in terms of the quantity of apples thus leading to lower prices than those observed at the beginning of the season. On the other hand, poor fruit quality is assumed to be associated with a bad harvest season, with a scarcity of fruit leading to higher prices. The range of purchase costs, price per kilogram, falls into empirical observations by processing plant managers. In the same table, π^ω represents the probability of each scenario and the "%" column is the relative increment for the purchase price at that second stage compared to the first-stage price. Regarding storage costs, CF^ω, these are considered to be 35% higher than CF^0 because most of the warehouses have already been assigned and the hiring costs tend to be higher. This storage cost behavior has been considered similarly for all the scenarios.

All tests were performed on a virtual scientific computing platform, known as Stormy, at the University of Lleida. More information about this infrastructure can be found in Stormy (2020). The virtual machine chosen for the experiments was configured with 10 virtual CPUs (QEMU Virtual CPU version 1.5.3) with 2.2 MHz, 25 GB of RAM and also 100 GB of Hard drive disk (HDD). The operating system used was Ubuntu 13.04. However, a typical laptop would be enough to run the model. The model was implemented using the Pyomo modeling language (Hart et al., 2011) in Python version 3.5. The main reasons for this selection are the flexibility, open-source feature, and potential of the Python language to deploy data manipulation and data representations. Thus, the model presented is not linked to a specific solver, so it can be solved using different ones, such as Cplex or Gurobi. In the literature, it is common to design, implement, and solve mathematical models in C/C++, A Mathematical Programming Language (AMPL), or Computational Infrastructure for Operations Research (COIN-OR) to achieve better computational time performance. Nevertheless, Python is a universal language that makes fast prototyping and is capable of building complex algorithms (decomposition methods, metaheuristics) exchanging information and data with solvers. Python programming is an excellent way to mix OR methods with data analytics and machine learning. To deal with end users and build useful decision support tools, it is necessary to build or integrate modules with legacy apps. Moreover, it is essential to implement Graphical user interface (GUI) or web apps and make communication with services and microservices such as Application programming interfaces (APIs) or databases more straightforward. Thus, using Python makes it simple to gather and retrieve input/output data and make data transformations and workflows in comparison with C. In this work, these features are more important than the reduction of performance between the implementations of C and Python. Thus, the model can be provided quickly with Python functionalities to feed and improve the development of DSS for the apple supply chain context. In this case study, the solver selected was Gurobi 7.0.2 (Gurobi, 2020), and this was configured to used parallel computing and all the available processors.

5.2. Results and discussion

5.2.1. Deterministic solution of single scenarios

On logical grounds, if the purchasing managers knew the conversion factor fc and market conditions beforehand, the decision would be easier to make at the beginning of the season. In that case,

Table 4
Number of producers selected as suppliers and percentage of utilization of the total storage capacity per scenario

		Usage of warehouses (%)										
		13 t	11.6 t	13 t	9 t	17 t	24.4 t	4.7 t	6.5 t	15.6 t	8 t	7.5 t
		CR	CR	CR	CR	SF	AC	CR	SF	AC	CR	CR
Ω	Producers	1	2	3	4	5	6	7	8	9	10	11
1	61	–	75	100	–	–	44	100	–	–	–	–
2	71	–	100	100	–	–	44	100	33	–	–	–
3	72	–	100	100	–	–	56	100	67	–	–	–
4	82	–	100	100	40	–	67	100	100	–	–	–
5	83	–	100	100	20	12	67	100	100	–	–	–
6	93	–	100	100	40	12	67	100	100	–	–	–
7	110	–	100	100	80	12	78	100	100	–	–	–
8	126	–	100	100	100	25	78	100	100	–	–	–
9	138	–	100	100	80	38	78	100	100	–	50	–
10	149	–	100	100	100	75	89	100	100	–	–	–
11	156	–	100	100	100	75	89	100	100	–	50	–
12	166	–	100	100	100	75	100	100	100	–	100	–
13	186	25	100	100	100	100	100	100	100	–	100	20

the optimal decision calculated from a deterministic model without considering uncertainty in fruit quality (*fc*), purchase cost, and storage contracts for each scenario is shown in Table 4.

Table 4 highlights the different outcome of dealing with a range of fruit qualities and unitary purchase costs represented by the scenarios (cf. Table 3). As expected, better quality of fruit means less raw material to purchase, fewer producers to agree contracts with and fewer warehouses to rent. We observe how the worst is scenario $\omega = 13$, with more producers selected, 186, and 10 warehouses rented. In particular, the number of producers selected ranged from 61 in scenario $\omega = 1$ to 186 and indicates the number of suppliers that would have to be selected under each scenario. Furthermore, the use of a warehouse on the same table not only marks the number of cold stores to be committed, from 4 ($\omega = 1$) to 10 ($\omega = 13$) required, but also the percentage of levels of use of current capacity. As a consequence of a declining quality of fruit worsening the *fc*, a higher number of warehouses is requested to increase storage capacity.

Moreover, Table 5 decomposes the total cost of ensuring the demand for purchasing storage and transport.The purchase and storage costs are presented in three components: the first-stage cost (1^{st}), the second-stage cost (2^{st}), and others (Others). The others cost represents the administrative cost, commitments with preferred producers, or the cost of using a specific cold store inside a warehouse. Generally speaking, the others costs represent all the costs belonging either to the purchase or the storage step, and are also independent of the stage. The results in Table 5 highlight that recourse actions without uncertainty in *fc* are useless. If the decision makers knew the unitary purchase cost at each stage, and the corresponding quality *fc*, they would always choose to purchase apples at the stage with the lowest cost. Because of that, the decision maker purchases the apples at the beginning of the harvesting season (first stage) or later (second stage), when they are cheaper (Table 5). Hence, for the first six scenarios, the second-stage unitary purchase cost is lower, so the outcome recommends purchasing at this stage. Otherwise, for the rest of the scenarios, the second

Table 5
Cost components and total cost of the deterministic solution for each scenario

	Cost in million of U.S. dollars ($M)							
	Purchase			Storage				
Ω	1st	2st	Others	1st	2st	Others	Transport	Total (tc^{ω})
1	–	0.334	0.001	0.002	–	0.080	0.056	0.473
2	–	0.477	0.001	0.003	–	0.093	0.065	0.639
3	–	0.588	0.001	0.003	–	0.107	0.075	0.774
4	–	0.777	0.001	0.004	–	0.126	0.084	0.992
5	–	0.822	0.001	0.004	–	0.133	0.093	1.053
6	–	0.945	0.001	0.005	–	0.147	0.103	1.201
7	1.228	–	0.001	0.006	–	0.160	0.112	1.507
8	1.401	–	0.002	0.007	–	0.173	0.122	1.705
9	1.513	–	0.002	0.008	–	0.187	0.131	1.841
10	1.645	–	0.002	0.009	–	0.201	0.140	1.977
11	1.738	–	0.002	0.010	–	0.214	0.150	2.114
12	1.851	–	0.002	0.012	–	0.228	0.159	2.252
13	1.964	–	0.003	0.014	–	0.241	0.169	2.391

stage is more expensive, and purchases are recommended in the first stage. Furthermore, all the storage contracts are signed in the first stage because signing storage contracts in the second stage has a penalty cost, mainly due to the risk of a future lack of storage. As the number of producers and warehouses increases when the quality of fruit worsens, the corresponding cost and transportation cost increase accordingly. Thus, the information displayed in the table can be summarized by saying that the deterministic model tends to sign all supply contracts when the purchase price is lower and the total cost increases as the scenario worsens. Tables 4 and 5 illustrate the decisions processing plant manager would make if they knew future prices and the conversion factor. As each scenario has a probability of happening, the expected cost of using the optimal solution for each scenario is a bound of the optimal value for the objective function in (1) and is known as the *WS* value (Birge and Louveaux, 1997).

5.2.2. Stochastic solution

The most important premise behind this study is that the quality of the apples (raw material) represented by fc and the purchase cost in the second stage (CC^{ω}) are uncertain. In particular, fruit quality (fc) is not known when the selected producers sign production contracts at the beginning of the season. Fruit quality may vary from season to season on a random basis and cause disruptions in cold-storage management and processing plant operation. For instance, if apples stored in SF run out, the CA chambers must be opened with the risk of ending long-term storage before the next season. Alternatively, an SF cold chamber for sale from a third party could be purchased to cover this disruption. So, this study is concerned with highlighting the advantages of the stochastic approach and the need for protection against uncertainty when planning the operation of a dehydrated apple processing plant. This stochastic approach represents an additional model complexity with a potential impact on solving times. Table 6 depicts the size of a single deterministic model

Table 6
Number of variables, constraints, and nonzero coefficients for the stochastic and deterministic models of one scenario in the case study

	Variables			Constraints			
Instance	(0–1)	$\mathbb{Z}$	$\mathbb{R}$	$\leq$	$\geq$	$=$	Nonzeros
Stochastic model	54,926	69,567	91,038	118,885	468	26,226	1,048,127
One scenario	7598	5352	7014	9145	36	2322	84,779

represented by one scenario and the size of the full stochastic formulation of the model involving $|\Omega| = 13$ scenarios.

The stochastic solution (*SS*) value also known the here-and-now solution (Escudero et al., 2007) corresponds to the objective function value of solving (1) and was \$1.56M. Although the deterministic model for one scenario was solved in a reasonable time (five minutes), that was not the case for the stochastic one. Moreover, the *SS* value was obtained with an execution time limit of one hour and a specific gap of 0.21%.

Different parameters have been proposed to measure the goodness of a stochastic approach concerning the related deterministic equivalent models (Birge and Louveaux, 1997; Ruszczynski and Shapiro, 2003; Wallace and Ziemba, 2005). The value of the stochastic solution (*VSS*) and the expected value of the perfect information (*EVPI*) were introduced for two-stage models (Birge and Louveaux, 1997). The *EVPI* compares the here-and-now (*SS*) with the *WS* approaches:

$$EVPI = SS - WS = SS - \sum_{\omega \in \Omega} \pi^{\omega} tc^{\omega}. \tag{4}$$

In our case study, the *EVPI* value was \$0.14M, which represents a reduction of 9% in the cost. This value is interpreted as the additional profit when we reach perfect information regarding the conversion factor and future purchase prices. It can be also understood as how much a processing plant manager is willing to pay to obtain perfect information on *fc* and *CC* for the season.

The *VSS* compares the here-and-now solution (*SS*) and the expected value (*EEV*) approaches by calculating $VSS = EEV - SS$. The following steps are required to calculate the *EEV* (Escudero et al., 2007):

1. solve the average scenario problem and keep the first-stage solution;
2. fix the previous first-stage solutions for all scenarios;
3. solve each scenario problem with the fixed first-stage solution;
4. calculate the *EEV* value as the expectation of the objective function over the set of scenarios.

To put this procedure into our context, let us assume that the purchasing managers always decide to purchase using the optimal amount according to the expected mean of the quality of the apples (raw material). Thus, the managers will use the stochastic approach with only the values of a mean scenario to compute a purchasing policy (*P*). Then, the managers using the policy (*P*) will know the optimal amount according to this expected quality. Next, we retain the first-stage solution of (*P*) and solve the problem for each scenario with a minimum cost (mv^{ω}). Thus, we can compute the

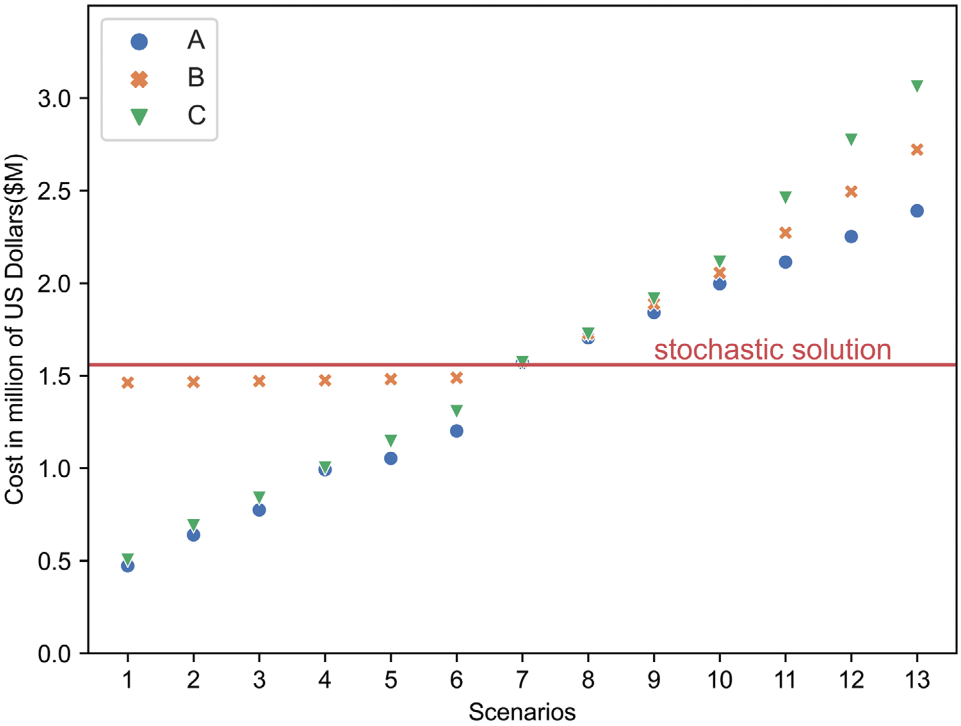


Fig. 4. Distribution of objective function per scenario (A) perfect information, (B) deterministic, and (C) stochastic solution.

overall cost according to the expected quality solution (EEV). The only requirement is to sum all these partial scenario costs (see Equation (5)):

$$EEV = \sum_{\omega \in \Omega} \pi^{\omega} mv^{\omega}. \tag{5}$$

The VSS represents the loss from not considering the random variations. Note that a large VSS means that the stochastic programming approach is able to exploit taking uncertainty into account in decision making. The evaluation of the VSS shows that the SS can reduce the costs by around 6.4%, due to the recourse actions. These results go beyond previously published results (Soto-Silva et al., 2017) thus demonstrating the advantages of using a deterministic model compared to the traditional methods used by the Chilean industry. Figure 4 gives additional insight. It shows how the minimum cost (tc^{ω}) is achieved in all scenarios under a perfect information approach (A), while if we ignore uncertainty and consider a deterministic approach (B) based on mv^{ω}, worse averaged weighted results are obtained than those from using the stochastic approach ($EEV > SS$). However, we can distinguish a different behavior per scenario depending on the second-stage market conditions comparing (B) and (C). This is, the first-stage solution of the average scenario problem in (B) impose much higher cost than in (C) when purchase prices at the second stage are

Table 7
Number of producers selected and the warehouse usage for each scenario according to the stochastic solution (*SS*)

		Usage of warehouses (%)										
Ω	Producers	13 t CR 1	11.6 t CR 2	13 t CR 3	9 t CR 4	17 t SF 5	24.4 t AC 6	4.7 t CR 7	6.5 t SF 8	15.6 t AC 9	8 t CR 10	7.5 t CR 11
1	47	–	100	100	40	–	44.4	100	66.6	–	–	–
2	51	–	100	100	20	12.5	44.4	100	100	–	–	–
3	63	–	100	100	40	12.5	55.5	100	66.6	–	–	–
4	72	–	100	100	40	12.5	66.6	100	66.6	–	25	–
5	74	–	100	66.6	80	25	66.6	100	100	–	25	–
6	88	–	100	100	100	25	66.6	100	100	–	–	–
7	101	–	100	100	80	25	77.7	100	100	–	75	20
8	118	–	100	100	80	37.5	77.7	100	100	–	75	20
9	133	–	100	100	80	62.5	77.7	100	100	–	75	0
10	139	–	100	100	100	37.5	88.8	100	100	–	100	40
11	147	–	100	100	100	75	88.8	100	100	–	100	–
12	164	25	100	100	100	100	100	100	100	–	100	80
13	176	25	100	100	100	100	100	100	100	–	100	100

Table 8
Objective function components for each scenario according to the stochastic solution (*SS*)

	Cost in million of U.S. dollars ($M)							
	Purchase			Storage				
Ω	1st	2st	Others	1st	2st	Others	Transport	Total
1	0.060	0.303	0.001	0.002	0.002	0.080	0.056	0.504
2	0.060	0.464	0.001	0.002	0.003	0.093	0.065	0.688
3	0.060	0.590	0.001	0.002	0.003	0.107	0.075	0.838
4	0.060	0.723	0.001	0.002	0.005	0.120	0.084	1.001
5	0.060	0.849	0.001	0.002	0.006	0.133	0.093	1.144
6	0.060	0.986	0.001	0.002	0.006	0.147	0.103	1.305
7	0.060	1.227	0.001	0.002	0.009	0.160	0.112	1.571
8	0.060	1.354	0.002	0.002	0.010	0.173	0.122	1.724
9	0.060	1.520	0.002	0.002	0.011	0.187	0.131	1.914
10	0.060	1.696	0.002	0.002	0.012	0.201	0.140	2.114
11	0.060	2.018	0.002	0.002	0.013	0.214	0.150	2.459
12	0.060	2.303	0.002	0.002	0.018	0.228	0.159	2.772
13	0.060	2.566	0.003	0.002	0.019	0.241	0.169	3.060

low. Otherwise, (B) shows slightly lower cost than (C) in scenarios where purchase prices are higher at the second stage.

Tables 7 and 8 summarize the results obtained from computing the *SS* presenting the information by scenario. Note that the *SS* results from applying the corresponding scenario probability, π^{ω}, to the total cost values per scenario (see Table 8). If we compare the results with regard to the number of producers selected in the *SS* in Table 7 (from 47 to 176) with the producers required with perfect information as shown in Table 4 (from 61 to 186), we observe that the *SS* reduces the range of producers selected in considering that the different scenarios may occur as a consequence of fixing the first-stage decision for all scenarios. In both cases, warehouse $c = 9$ is never used.

On the one hand, Table 8 shows how second-stage decisions regarding purchases and the renting of storage are more important than those in the first stage. We can interpret the importance of the recourse actions to adapt decisions to the uncertain scenario. In addition, purchase, storage, and transportation need to increase as the quality represented by the conversion factor of the product worsens, resulting in higher transport cost. Thus, the applicability of a deterministic model in a real context, using real data to assist processing plant managers was proven useful. By comparing the results extracted from Soto-Silva et al. (2017) with the ones presented in this work, feeding the stochastic model with the same input parameters, we observe that the stochastic model proposed in this study performs better. It provides a better solution and offers better support to the processing plant manager when minimizing the overall cost. The only drawback already mentioned is the computational time consumed to obtain the stochastic solution. These results are also in agreement with the improvement reported by Paam et al. (2019) using a different approach for an Australian apple company. Even though Paam et al. (2019) propose a deterministic model, the utility of the model relies on the behavior of the real system or the degree of uncertainty around similar activity in Australia or Chile.

5.3. Intended use of the model

The discussion in this study revolves around how the purchasing managers can mitigate the drawback of the uncertain raw cost and conversion rate *fc* when signing purchase and storage contracts. Given the impact that an inaccurate *fc* has on the company's purchase plan (cf. problem description in Section 3), the stochastic model offers an approach to protecting purchase managers from the uncertainty through recourse actions: purchasing additional fruit and renting additional cold storage.

5.3.1. Purchase decisions

The optimal solution of the model determines the selection of suppliers with the view to minimizing the purchase cost of the fruit including the producer's administration costs and the transportation cost from the orchards to the processing plant. The analysis of the optimal purchase plan can also provide practical information, useful for identifying the most preferred suppliers, that is, producers who always take part as suppliers selected across all scenarios. An example is presented in Fig. 5 where the 279 producers are represented by a table with 20 producers (0–19) per row. This figure maps the array of 279 producers (plus a blank cell) into a matrix of $m \cdot n$ cells ($m = 14$, $n = 20$), where the x-axes (n) represents ranks of 20 producers indexed from 0 to 19. The y-axis (m) represents the number of ranks of 20 producers. Each cell in the matrix informs about the apple variety available from the corresponding producer (by a different color) and which of these varieties are purchased regardless the scenario (cross marker) or not (dot marker). The cross marker highlights the purchases made in all scenarios and serves to identify key producers for the processing plant,

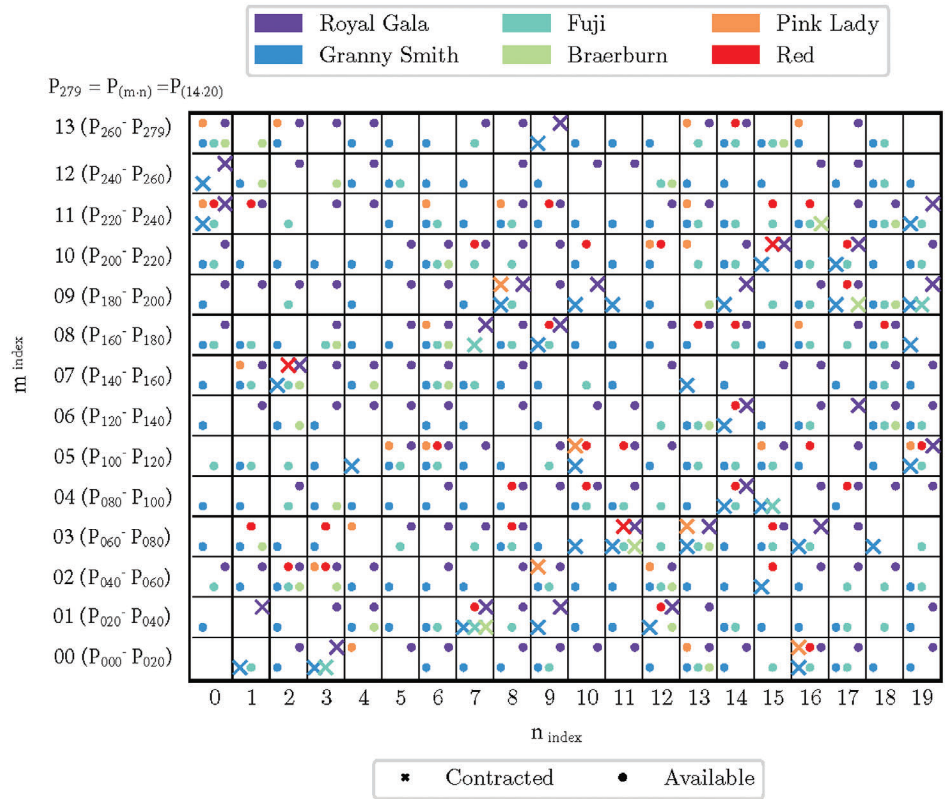


Fig. 5. Grid representation of the 279 fruit producers with corresponding varieties available for supply in color. Dot marker: varieties still available. Cross marker: varieties purchased in all scenarios. Note that each row (0–19) represents 20 suppliers.

that is, 39 producers in this case study. For example, producer number one (first row, second column) can supply two varieties (Granny Smith and Fuji), but in all scenarios the Granny Smith is selected. Note that the Fuji variety could be also selected from this producer in some scenarios not represented here, since Fig. 5 concerns only common decisions to the entire set of scenarios. Thus, purchase managers can act quickly at the beginning of the season to arrange stable agreements, for example, long-term purchase contracts for specific varieties. If this were not possible, it would be advisable to give priority to negotiating every season or envisaging additional rewards for these producers because of the fierce competition among packing and processing plants to ensure enough fresh fruit.

At any time, the processing plant manager can value the conversion rate, keep track of market prices, and proceed accordingly or postpone recourse actions to the second stage. So, the original purchase plan derived from the optimal solution can be implemented fully or partially depending on the evolution of the harvest. A new run of the updated model would allow managers to revise, confirm, or amend the original purchase plan. In addition, available suppliers can be also updated, selected, or deselected, according to the progress of the season. Once the harvesting season has finished, the uncertainty of the quality of the apples, their purchase cost, and the rental cost of

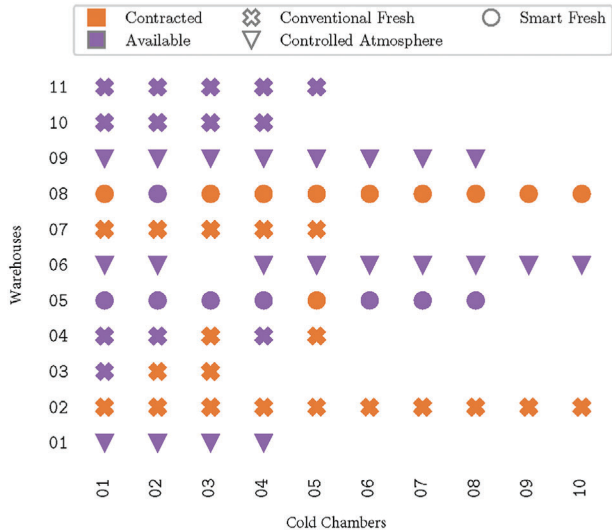


Fig. 6. Cold chambers rented in all scenarios (in orange) or still available (in purple) are arranged in rows (i.e., warehouses) and with shapes indicating the cold technology.

warehouses will have been revealed, and a deterministic model for the corresponding scenario can produce corrective actions if the conversion factor of the apples worsens.

5.3.2. Storage contract decisions

According to the purchase plan, enough storage room is necessary to preserve all the purchase. Therefore, the optimal solution of the model gives the storage plan with required contracts to sign to minimize storage and transportation cost. Figure 6 depicts the storage plan showing the storage resources rented at the first stage in all the scenarios. This figure shows the number of cold chambers available in each warehouse by an icon related with cold technology. The main information relates to the contract of a chamber represented by a cyan color while cold chambers not contracted are in orange color. Only storage resources rented in all the scenarios at the first stage are colored. The cold stores rented across all scenarios are shown in orange, among them two warehouses (#2 and #7) for conventional fresh fruit with full facilities rented. Figure 6 complements the information in Fig. 3 about the storage resources allocated by the model. Finally, orange is used to highlight the ones the model selects in all scenarios. For example, it does not matter which conversion factor is revealed in this study because all the chambers available from warehouse number two are chosen. Depending on the scenario, additional warehouses or chambers would be contracted. For instance, comparing the information shown on Table 7 with Fig. 6, the need to contract warehouses W02 and W07 is consistent while W09 is never requested. Thus, the solution allows the processing plant manager to obtain an overall image of all the actors involved and establish new relations and price negotiations with common actors (supplier or warehouses) and plan better regarding opening and closing of cold stores using the percentage of usage and the cold-storage technology.

The model is expected to be used with a rolling horizon. The planning of the dehydrated processing plant operation has to be set by the plant manager before the harvesting season starts. So, the first run would be around the beginning of the harvesting season, when estimates of the quantity and quality of the fruit on the trees and prospects of the market allow the manager to agree a purchase price and supply conditions with the producers. All producers and cold-store rooms are available for contracts. Hence, the optimal solution would lead to the implementation of first-stage decisions. In this context, a chart like Fig. 5 may help to identify and prioritize the producers appearing in all the scenarios when agreeing purchase contracts.

As the harvesting season can be three months long due to late varieties, an update of the parameters of the model would be advisable in mid-season, as more precise information about apple quality, quantity, and the evolution of market prices becomes available. This second run could confirm or refine the initial solution. The last run of the model could be done at the end of harvesting season to confirm the needs for additional purchases or cold stores. The harvest season gives the manager the opportunity to update the parameters in the model and adapt the solution according to the performance of the processing plant during this period. Thus, after starting to process the fruit, the quality of apples can be valued and the second-stage decisions can be proceeded with signing the remaining contracts to ensure the operation of the processing plant through to the next season.

At any time, the processing plant manager can postpone second-stage decisions or implement them partially, and rerun the model and confirm or amend the original plan selecting or deselecting new producers according to the progression of the season. Once the harvesting season has finished, the uncertainty of the quality of the apples, the purchase cost, and rental cost of warehouses will have been revealed, and a deterministic model for the corresponding scenario can produce eventual second-stage decisions that could be updated if the conversion factor of the apples worsens. This may lead to considering a multistage stochastic problem to cover all the stages where a decision may make sense.

6. Conclusions

In this paper, we propose a two-stage stochastic programming model aimed at supporting tactical decision making regarding supplier selection and storage contracts in ASCs like FSC. The literature review reveals few proposals that apply stochastic optimization in ASC where most decisions still rely solely on managers' experience and know-how.

The general model was evaluated based on a case study with real data from a Chilean dehydrated apple processing plant. This study illustrates the advantages of the model for minimizing production costs, fixing a purchase and storage plan while meeting the demand for dried apple. Uncertainty in the conversion factor of the fresh fruit into processed product and market prices are represented by scenarios. The optimal solution enables processing plant managers to prioritize and select suppliers and storage facilities in the first stage and to complement these decisions with recourse actions in the second stage. $EVPI$ and VSS approaches showed that additional information would save 9% of $EVPI$ costs, while the VSS might reduce costs by 6.4% compared with the deterministic solution.

The structural similarities between FSC and other ASCs regarding purchasing, warehousing, and processing of fresh fruit broaden the applicability of the proposed model beyond FSCs. For instance, this could extend to processing plants producing canned fruit, juice, dried vegetables, frozen fruits, and vegetables, etc. There are some features in the usage of the proposed model that can become drawbacks. First of all, although the computational time of *VSS* was affordable, around one hour with a gap of 0.21%, it would be expected to be greater with larger instances and commit applicability in larger instances. Second, the results depend on the parameters and scenario, so they must represent the specific processing plant to really assist the processing plant manager with the selection of suppliers and the renting of storage facilities to meet the season's demand for dried apples.

The harvest season lasts three months due to late varieties. This gives the manager the opportunity to update the parameters in the model and adapt the solution according to the performance of the processing plant during this period. An update of the parameters in the model would be advisable in mid-season, as more precise information about the apple conversion rate, harvest quantity, and the evolution of market prices would be available. Thus, after the processing of the fruit has started, the quality of the apples can be valued and then proceeding with the second-stage decisions and the signing of the rest of contracts to ensure the operation of the processing plant until the next season. This rolling horizon can confirm or refine the initial solution. A final run of the model could be done at the end of the harvesting season to confirm the purchase plan and cold-store renting. Furthermore, another interesting research direction should be the risk-aversion decision models. The model presented is a potential candidate to be evaluated, updating the objective function with a conditional value-at-risk approach. Thus, the decision maker can obtain a complete picture of the risks, leading to a more conservative approach in terms of risk exposure and price uncertainties. Finally, the model has a limitation in that it considers a fixed-price distribution for the second stage. Future work should consider different price distributions to give decision makers the ability to use price promotion and discount strategies in their negotiations. On the other hand, it could be interesting to introduce more stages into the stochastic model to include more operational decisions in the timeline and grant the plant manager a more accurate view. Furthermore, another attractive option would be integration risk aversion into the modeling strategy to extend the case study and compare results. Other research paths that are less practical and related to the computer science field would be to improve the solver solution by using advanced computer science techniques (parallel computing or AI algorithms) to decompose the scenarios. These include Lagrangean decomposition, progressive hedging, or metaheuristics to reduce further the computational time required to obtain the optimal solution in larger instances.

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